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The AFIT Gross Motion Control Project

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ABSTRACT

The objective of the Gross Motion Control project at the Air Force Institute of Technology (AFIT) Robotic Systems Laboratory is to investigate alternative control approaches that will provide payload invariant high speed trajectory tracking for non-repetitive motions in free space. Our research has concentrated on modifications to the model-based control structure. We are actively pursuing development and evaluation of both adaptive primary (inner loop) and robust secondary (output loop) controllers. In-house developments are compared and contrasted to the techniques proposed by other researchers. The case study for our evaluations is the first three links of a PUMA-560. Incorporating the principals of multiple model adaptive estimation, artificial neural networks, and Lyapunov theory into the model-based paradigm has shown the potential for enhanced tracking. Secondary controllers based on Quantitative Feedback Theory, or augmented with auxiliary inputs, significantly improve the robustness to payload variations and unmodeled drive system dynamics. This paper presents an overview of the different concepts under investigation and provides a sample of our latest experimental results.

1 Introduction

An initiative at the Air Force Institute of Technology (AFIT) Robotic Systems Laboratory is the development, analysis, and experimental evaluation of intelligent robotic manipulator control algorithms. The motivation for our research is the high degree of tracking accuracy and environmental compliance required by future aerospace applications like robotic telepresence and automated flightline maintenance. The requirement for accurate high speed tracking with variable payloads can not be satisfied by classical individual joint feedback control schemes. Advanced control concepts that utilize knowledge of manipulator system dynamics are required. Those approaches must be robust and/or adapt to variations in manipulator dynamics caused by model inaccuracies, payload variation, and environmental interaction.

The objective of the Gross Motion Control project is to investigate alternative control approaches that will provide payload invariant high speed trajectory tracking for non-repetitive motions in free space. Our research has concentrated on modifications to the model-based control structure. Techniques for improving model-based controller performance can be divided into two groups based on whether they concentrate on the feedforward or feedback portion of the algorithm. AFIT is actively pursuing development and evaluation of techniques in both areas. The test case for our studies is the first three joints of a PUMA-560. The PUMA's well known design limitations provide a challenging control system design problem. Any algorithm that performed well on PUMA will work even better on the modern designs that will inhabit future flightlines. This paper provides an overview of the concepts being investigated and presents some of our latest results. Detailed information is contained in the numerous references.

This overview is organized as follows. In section two we describe the experimental evaluation environment and the control algorithm used to provide a tracking performance baseline. Section three discusses the development and evaluation of three forms of adaptive feedforward compensation while section four serves the same function for robust feedback and auxiliary input concepts. Conclusions and on-going research are the subject of section four.

2 Experimental Environment

The need to operate on equipment designed for human maintenance focuses our efforts on controllers for vertically articulated robotic systems with high torque amplification drive systems. While the modeling of link dynamics is well understood, complete modeling of drive system dynamics is difficult, if not impossible, for geared or harmonic transmissions. The motor and transmission dynamics of high torque drive systems play a major role in manipulator system dynamics [15, 18]. Therefore, the true performance potential of advanced robotic control concepts can only be determined through experimental evaluation and analysis. The experimental evaluations performed in this study were conducted under the AFIT Robotic Control Algorithm Development and Evaluation (ARCADE) environment [15]. Unless otherwise noted the algorithm servo rate is 222 Hz.

The goal of our experimental control algorithm evaluations is to validate concepts, not produce the optimum PUMA specific algorithm. Evaluations are conducted over operational configurations that excite all the manipulator's dynamical interactions so that general conclusions about algorithm performance can be drawn. Motion from $(-50°, -135°, 135°)$ to $(45°, -90°, 30°)$ in 1.5 seconds excites all the dynamics [15]. Robustness to payload variation is evaluated by attaching a series of brass disks to the sixth link mounting flange. The additional payload produces a significant change in inertial and gravitational dynamics [17, 15].

The general form of the output torque vector (τ) for a model-based control algorithm can be divided into feedforward (τ_{ff}), feedback (τ_{fb}), and auxiliary input (τ_{ax}) components.

$$\tau = \tau_{ax} + \tau_{ff} + \tau_{fb} \tag{1}$$

Each of the five techniques discussed in this paper modifies only one of those components. The actual algorithm that controls future robots will probably have modifications to all three components but first we must understand how they function independently.

All the algorithms were implemented on a digital computer. The delay inherent in a digital implementation is handled by using the error information from the previous sample time in the current cycle output torque calculations. A single (non-adaptive) model-based control (SMBC) algorithm with complete feedforward dynamic compensation and fixed PD gains provided the performance baseline for our evaluations.

$$\tau_{ff}(k) = [\hat{D}(q_d(k), \hat{a}) + J_{eff}]\ddot{q}_d(k) + \hat{h}(\dot{q}_d(k), q_d(k), \hat{a}) + B_{eff}\dot{q}_d(k) + \tau_s + \hat{g}(q_d(k), \hat{a}) \quad (2)$$

$$\tau_{fb}(k) = K_v\dot{e}(k-1) + K_p e(k-1) \quad (3)$$

$$\dot{e}(k-1) = \dot{q}_d(k-1) - e(k-1)/T_s \quad (4)$$

$$e(k-1) = q_d(k-1) - q(k-1) \quad (5)$$

where: ˆ represents modeled values, and the the feedforward and feedback components are identical to the configuration employed in previous research [15].

3 Adaptive Feedforward Compensation

Three adaptive feedforward compensation techniques are in various stages of development and evaluation. In all cases the feedback loop τ_{fb} has been fixed to the same gain set used for the SMBC baseline. Fixing the feedback allows the performance improvement from adaptation to be isolated and analyzed. All three algorithms have adaptation mechanisms that are drive by trajectory errors so they can be considered as direct forms of adaptive control. Discussion will start with the most mature algorithm, adaptive feedforward compensation based on Lyapunov theory [14].

3.1 Adaptive Model-Based Control

Slotine and Li proposed an approach to adaptive model-based control (AMBC) that uses parameter adaptation based on Lyapunov theory to compensate for model-based controller limitations [27, 28]. An excellent tutorial on adaptive model-based control based on Lyapunov theory is in [22]. Successful experimental evaluation on the MIT WAM robot [21] provided the motivation for our investigation into the feasibility of the direct adaptive model-based concept for a manipulator with: high torque amplification drive system, slower peak velocities, and variable payloads.

In our initial evaluation of the AMBC concept we implemented the first control formulation proposed in [28]. The resultant AMBC algorithm had excellent tracking performance for the zero payload case and excessive endpoint error in the presence of payload uncertainity. The adaptation mechanism was also ineffective for slow trajectories [10]. The next logical step was to implement the full sliding mode version of the Slotine and Li approach [28]. However, the inclusion of the position and velocity measurement noise into the regressor produced unacceptable levels of vibration. To eliminate that problem, and separate the performance improvement due to sliding mode feedback and parameter adaptation, we implemented a version of the "Desired Compensation Adaptive Law" [20]:

$$\hat{\theta}(k) = \int_0^{T_s} \Gamma^{-1}Y_1^T(q_d(k), \dot{q}_d(k), \ddot{q}_d(k))[(\dot{e}(k-1) + \Lambda e(k-1)] \quad (6)$$

where T_s is the sample period and the integration was accomplished using the Adams-Bashforth Two-Step method as described in [4]. The adaptation mechanism now has the capability to drive the position error asymptotically to zero and regressor dependence on actual trajectory information is eliminated. An additional implementation advantage is the ability to precompute the regressor for known trajectories [20]. The basic structure of the adaptive control law remains unchanged:

$$\tau_{ff}(k) = Y_1[q_d(k), \dot{q}_d(k), \ddot{q}_d(k)]\hat{\theta}(k) + Y_2[q_d(k), \dot{q}_d(k), \ddot{q}_d(k)]\hat{\theta}_n(k) \quad (7)$$

where Y is the regressor matrix and $\hat{\theta}_n$ contains the "known" parameters and $\hat{\theta}$ contains the estimated parameters. The regressor is based on the known structure of the manipulator system dynamics and includes reflected actuator inertias and viscous and coulomb friction [14]. All $\hat{\theta}_n$ parameters were initialized to directly correspond to the nominal values used in our previous studies [15, 18]. The Λ matrix was diagonal with components $\lambda^i = k_P^i/k_D^i$, where k_P^i and k_D^i represent the diagonal terms of the position and derivative feedback gain matrices respectively.

AMBC tuning is a very heuristic procedure which is dependent on: the manipulator, the number of adaptive parameters, and the individual components of the Γ^{-1} matrix. The simple selection of a diagonal Γ^{-1} matrix can result in improved performance or disaster. The relative magnitude of the individual Γ^{-1} elements can vary widely, and aggressively adapting certain parameters can cause instability. In order to maximize algorithm performance and maintain stability we employed a rigorous three step tuning procedure [14].

There was a definite correlation between maximum tracking performance and the size of the $\hat{\theta}$ vector. Sixteen parameters was the magic number for our implementation. An interesting observation was that the amount of parameters, degrees of freedom in the space, not their physical significance was the important factor [14]. The adaptation law uses the available degrees of freedom to find the location in the parameter space which produces the minimal overall error for the three joints. Our results are consistent with another AMBC study were the authors found they could eliminate any knowledge of viscous and coulomb friction forces from the regressor and retune the adaptation law to compensate [5]. Investigations to further explore the generality of this hypothesis are underway.

The first step in the evaluation process was to baseline our controller over the standard evaluation suite. The parameter vector $\hat{\theta}$ was initialized prior to each test to a set of nominal values based on our a priori knowledge of zero payload manipulator system dynamics [17, 15]. Figures 1-6 highlight the tracking performance for both zero and 2 Kg payloads. AMBC clearly demonstrates the ability to compensate for uncertainties in drive system dynamics and end-effector payload.

A comprehensive evaluation of AMBC capabilities is underway. Investigations into the effects of: learning, parameter initialization, and feedback gains on algorithm performance have revealed that [14]:

- A short initial zero payload training phase permits the controller to learn the unmodeled drive system dynamics and errors in nominal inertial parameters. Continual learning does not hinder the algorithm's ability to adapt to variations in operational conditions.

- Transient performance during learning can be unpredictable even after initial training.
- For maximum tracking performance the adaptation processes should not be disabled. The controller modifies the parameter set over the course of the trajectory even after the learning phase.
- While the adaptation ability of the AMBC is impressive, for maximum tracking performance there is still no substitute for good nominal parameter information.
- Instead of learning the actual values, the adaptation mechanism learns the effect of the parameters on the tracking error and reacts accordingly.
- Softer PD gains reduce the robustness of any model-based algorithm to payload uncertainity and model mismatch. AMBC was no exception. However, the ability to learn nullifies the high gain advantage.

The performance of an AMBC algorithm should be carefully monitored over the expected operational range to assure that transients are within specifications. The desired trajectories should also be checked for actuator constraints such as saturation or jerk limitations. Either of those constraints can produce tracking instability.

3.1.1 Multiple Model-Based Control

An alternative to the Lyapunov based approach is the use of stochastic estimation/adaptation techniques. In addition to providing a fast means of parameter adaptation the stochastic approach explicitly accounts for the numerous sources of noise and uncertainty in a real physical system. Multiple Model Adaptive Estimation (MMAE) is a Bayesian estimation approach that employs multiple Kalman filters to quickly and accurately estimate parameters in the presence of noise and uncertainty. By combining the principles of MMAE and model-based control a powerful new form of adaptive model-based control was developed [13].

The Multiple Model-Based Control (MMBC) technique utilizes knowledge of nominal plant dynamics and principles of Bayesian estimation to provide a high degree of tracking accuracy in uncertain payload configurations. The MMBC algorithm is formed by augmenting a model-based controller with a form of MMAE. The MMAE algorithm is tuned to provide an estimate of the payload parameter ($\hat{a}$). The model-based controller combines the a priori knowledge of nominal structure with the parameter estimate to produce the multiple models of the robot dynamics required to maintain tracking accuracy.

The basic premise of the MMAE technique is that the continuous parameter vector $\mathbf{a}$ can be discretized into a finite set of possible vector values, $(\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_K)$. The discretization of $\mathbf{a}$ must be large enough that there is a discernible difference between the models but not so large as to induce unacceptable errors in the estimate. The MMAE is composed of $\mathbf{K}$ Kalman filters running in parallel, each of whose plant models is based upon an assumed parameter $\mathbf{a}_k$. At the ith sample time, the measurement is passed to each of the filters. The residuals generated by the $\mathbf{K}$ filters are used to calculate the hypothesis conditional probabilities. These probabilities are used as weighting factors to generate $\hat{\mathbf{a}}$. Additional information about the principles of Multiple Model Adaptive Estimation can be found in [13, 19].

Figure 7 provides a sample of the experimental error profiles for the MMBC technique. The servo period for those evaluations was 100 Hz. Experimental evaluations have validated the simulation studies and clearly demonstrated the algorithm's potential to adapt to payload variations [13]. The MMBC approach is the most computationally complex algorithm we have evaluated, and the level of tuning difficulty is on the same order of magnitude as the Lyapunov technique. Additional research is required to determine any advantages that this method may have over the neural network or Lyapunov based concepts.

3.2 Neural Network Payload Estimation

Our concept for integrating the principles of artificial neural networks and model-based control was initially developed and experimentally evaluated for the relatively simple motions of a single vertically articulated joint [8]. Previous experiments examined the Adaptive Model-Based Neural Network Controller (AMBNNC) with varying payloads, initial conditions, and payload update rates. Those experiments showed that a Neural Network Payload Estimation (NNPE) algorithm can quickly and accurately identify payload variations from manipulator tracking error patterns. The three DOF extension was not a trivial extrapolation of our initial research and provides valuable insights into the utilization and training of ANNs for robotic control [12].

Both the MMBC and AMBNNC algorithm development started with the assumption that a reasonably accurate model of system dynamics was available. If no a priori model information is available off-line techniques can be employed to determine one [9]. Neural Network Payload Estimation (NNPE) provides a mechanism by which the payload dependence of the model-based control paradigm is reduced [8, 12]. The Adaptive Model-Based Neural Network Controller (AMBNNC) uses the output of a NNPE to adapt the feedforward dynamic compensation torques to payload variation or other disturbances that might increase tracking error. The feedforward compensation is identical to Equation (2) with the provision that the $\hat{a}$ values are now the payload parameter vector estimate produced by the NNPE.

The particular form of NNPE currently being investigated uses multilayer perceptron (MLP) artificial neural networks (ANNs) to determine the payload mass parameter. One neural network is trained and used for each individual update time of the trajectory. The neural networks consisted of (6) input nodes, (12) nodes in each of two hidden layers, and (5) output nodes. Training was performed using the same techniques and performance measurements as for the single link case [8]. To generate a representative set of training data for the multi-joint NNPE, the manipulator was run through the 3 DOF test trajectory ten times for each payload condition producing 121 training exemplars [12]. Instead of four payload payload classes with only positive payload variation the multi-joint NNPE was trained for five payload classes representing negative two to positive two kilogram variations. The step size remained at one kilogram and the desired value was still 0.9 for the actual class. Trained networks were tested in feedforward operation using vectors of position information not previously seen by the networks. Accuracy and error were calculated the same as during training tests. The trained neural nets were then ready for on-line operation and evaluation.

The augmentation of a model-based controller with a NNPE algorithm definitely improves overall tracking performance, but payload invariance has not yet been obtained [12, 11]. Current research is concentrated on removing the restrictions that limit AMBNNC performance to levels noticeably below the AMBC. Alternative paradigms for training the multilayer perceptron network are under investigation and replacing the MLP with a more sophisticated ANN is under consideration. The amount of adaptive parameters will also be increased. AMBC analysis revealed that adaptive algorithm performance was strongly correlated to degrees of freedom in the parameter space. Although the current AMBNNC implementation modifies the entire payload vector only the mass parameter is adapted. The ability to eliminate the dependence on heuristic tuning and the potential displayed by the single parameter adaptation are the motivation for our continued research in this area.

4 Feedback Compensation

Inconjunction with the adaptive feedforward evaluations two forms of feedback compensation under investigation. Both methods were mature enough to be compared against the performance of the AMBC approach over the standard evaluation suite. Those evaluations show that all three methods offer a comparable level of tracking accuracy.

4.1 MBAIC

In a series of publications Seraji has presented the development of an improved Lyapunov-based Model Reference Adaptive Controller (LB-MRAC) [24, 25, 23]. His initial PUMA evaluations were conducted without feedforward adaptation over a very slow trajectory [25]. We replicated those results and then evaluated several version of the algorithm over the standard test suite [16]. Without feedforward compensation LB-MRAC tracking accuracy is inferior to SMBC and, if the PD gains are initialized to a reasonable value, the the effect of gain adaptation is negligible. The real power of the technique is in the robust properties of the auxiliary term. Apparently Seraji also came to that realization and proposed a robust technique that incorporates an adaptive gain auxiliary input, fixed PD feedback, and the nominal dynamic feedforward compensation of a model-based controller [26]. As an example of the potential from augmenting a model-based structure with an auxiliary input we implemented a version of his approach.

Model-Based Auxiliary Input Control (MBAIC) is formed by augmenting a model-based controller with an auxiliary input based on Lyapunov theory [16]. The feedforward compensation (τ_{ff}) and feedback (τ_{fb}) are not altered. No gain adaptation is employed. MBAIC produced tracking accuracy superior to the pure LB-MRAC concept and the SMBC baseline [16]. The exact form of the auxiliary input depends on the techniques employed to calculate the velocity error and perform the digital integration. A τ_{ax} input expressed as:

$$\begin{aligned}\tau_{ax}(k) \;=\; & \mu_1 w_p \frac{T_s}{2}[e(k-1)+e(k-2)] + \\ & \mu_1 w_v \frac{T_s}{2}[\dot{q}_d(k-1)+\dot{q}_d(k-2)] + \\ & \mu_1 w_v \frac{1}{2}[q(k-3)-q(k-1)] \qquad (8)\end{aligned}$$

accounts for the one time step delay in error information due to our digital implementation and produced the best response [16]. Application of the MBAIC on the PUMA did not exhibit any symptoms of integrator windup. Therefore the inclusion of a "σ modification" [26] in the auxiliary term would only degrade tracking accuracy.

Figures 1-6 highlight MBAIC tracking efficacy. Addition of an auxiliary input significantly enhances model-based controller tracking accuracy and eliminates the large end-point error previously associated with operation in uncertain payload configurations. MBAIC has the potential to support both high speed trajectory tracking and environmental compliance by shifting the stiffness required for accurate gross motion control to a switchable auxiliary input. The main limitation with the MBAIC concept is the tuning process.

The starting point for our MBAIC tuning was the auxiliary input design parameters specified by Seraji [25]. The amount of time devoted to arriving at those parameters is unknown but efforts to improve the tracking by increasing the w_p and w_v values only produced increased levels of vibration. We were able to improve performance slightly by selecting the μ_1 values individually for each joint [14]. Searching the parameter space for a good set of PID gains is a non trivial task and we suspect that MBAIC tuning requires a similar degree of heuristic effort.

4.2 MBQFT

Quantitative Feedback Theory (QFT) is a frequency domain design procedure which has been successfully applied to the problems of robust flight control [7, 6]. The superior performance of the QFT in those applications motivated our investigation of a robotic implementation [1, 3]. An introduction to QFT design, and a comprehensive set of references can be found in [6]. Application to a robotic system required the development of a pseudo-continuous time (PCT) analog QFT design procedure. The combination of nonlinear feedforward compensation and PCT-QFT feedback is referred to as a Model-Based Quantitative Feedback Theory (MBQFT) controller [1, 3]

Since the PUMA case study is a 3x3 system, a 3x3 QFT multiple-input, multiple-output design was used. The 3x3 system was decoupled into three equivalent MISO loops and the interactions between the joints were modeled as disturbances. The MBQFT design evaluated in this study was based on seven plant templates equally spaced over the fast standard trajectory. The nominal feedforward compensation allows a linear QFT design to be used. The robot dynamics were linearized based on a zero payload configuration. The analog design is converted to the digital domain by an exact Z-transform and proper scaling of the control law. The feedback controller for joint one was third order over third order in the z-plane, the joint two and three controllers were fourth order over fourth order. The actual feedback control torques were produced by backwards difference equations [1, 3]:

$$\begin{aligned}\tau_{fb}(k) \;=\; & A_3\hat{e}(k) + A_2\hat{e}(k-1) + A_1\hat{e}(k-2) + A_0\hat{e}(k-3) \\ & -B_2\tau_{fb}(k-1) - B_1\tau_{fb}(k-2) - B_0\tau_{fb}(k-3) \qquad (9)\end{aligned}$$

$$\begin{aligned}\tau_{fb}(k) &= A_4\hat{e}(k) + A_3\hat{e}(k-1) + A_2\hat{e}(k-2)A_1\hat{e}(k-3) \\ &+A_0\hat{e}(k-4) - B_3\tau_{fb}(k-1) - B_2\tau_{fb}(k-2) \\ &-B_1\tau_{fb}(k-3) - B_0\tau_{fb}(k-4) \qquad (10)\end{aligned}$$

Equation (9) was used for joint 1 while joint 2 and 3 feedback was of the form of Equation (10).

The analog design is based on instantaneous position error information. The unmodeled one sample period delay inherent in a digital implementation was accounted for with an error estimator.

$$\hat{e}(k) = e(k-1) + (\dot{q}_d(k-1) - \dot{q}(k-1)) * T_s \qquad (11)$$

The key benefit of this approach is that analog design procedures could be used while still considering the digital effects (primarily, sampling delays). The additional on-line computational requirements, as opposed to the standard PD feedback control law, are minimal.

While algorithm development may be mathematically rigorous, tuning is usually based on heuristics. The key difference between the MBQFT and the other methods is that QFT design and tuning techniques are both well defined [6]. QFT synthesis provides an excellent initial set of controller coefficients and employs classic control tradeoffs such as giving up gain for phase margin to further tune performance [1, 3]. Empirical studies have revealed that designs based on the nominal robot dynamics tend to overstate the gain requirement [2]. If the gain is high enough to cause vibration on the robot, some phase margin must be given up to decrease the gain. The initial MBQFT controller caused excessive arm vibration due to high gains. However, only three design iterations were required to achieved the level of performance shown in Figures X-Y.

The MBQFT technique provides high speed trajectory tracking performance that is robust to small payload variations and unmodeled drive system dynamics. Replacing the τ_{fb} block with feedback laws based on PCT-QFT design resulted in up to a factor of four improvement in tracking accuracy. The non-heuristic nature of the MBQFT design and the computational simple implementation makes this approach an attractive alternative for a wide range of industrial manipulators.

5 Conclusions

The Gross Motion Control project has produced a new level of understanding about the control techniques necessary to provide the high level of trajectory tracking performance required for future Air Force applications. Model-based control can be made robust to incomplete dynamics modeling and payload uncertainty and is therefore a suitable structure for intelligent control algorithms.

Incorporating a desired compensation adaptation law, robust feedback, or an auxiliary input produced a model-based controller with payload invariant tracking for the first two joints of the PUMA. Therefore, the selection of "best" concept for enhanced tracking will depend on factors other than tracking performance. The two main considerations are tuning and computation time. While the adaptive approaches are more computational intensive the ever increasing power of modern microprocessors makes small variations in algorithm complexity a mute point. However, the tuning issue is very real and can not be ignored. The MBQFT has a distinct advantage in this area that neural networks may offset. The MBQFT design and tuning procedures are mathematically well defined and can be related to the well known parameters of gain and phase margin. For that reason we recommend the MBQFT technique for industrial applications with small payload variations. The learning capabilities and compliance potential of adaptive model-based control may be more appropriate for human arm emulation.

While are results are very promising there is still research to be done in this area. Continued development and evaluation of the AMBC and AMBNNC techniques is in progress. A compliant form of AMBC is also under investigation. Techniques for replacing the entire feedforward compensator with a neural network are being developed. Once the digital control system for the Utah/MIT had is operational we will extend our gross motion control research to that platform. Comparison between PUMA and hand evaluations will highlight the effects of manipulator dynamics and actuator systems on advanced controller tracking performance.

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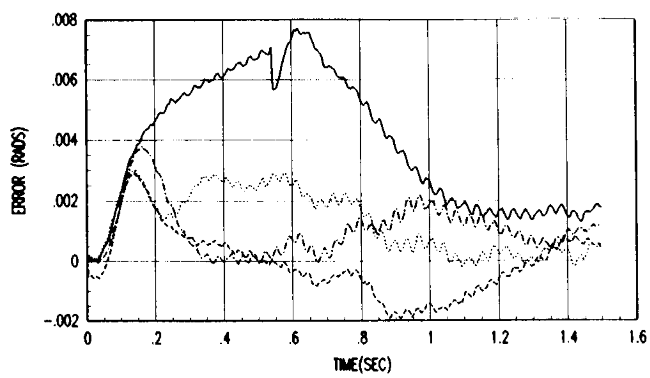

Figure 1: Joint 1 Tracking Evaluation w/o Payload

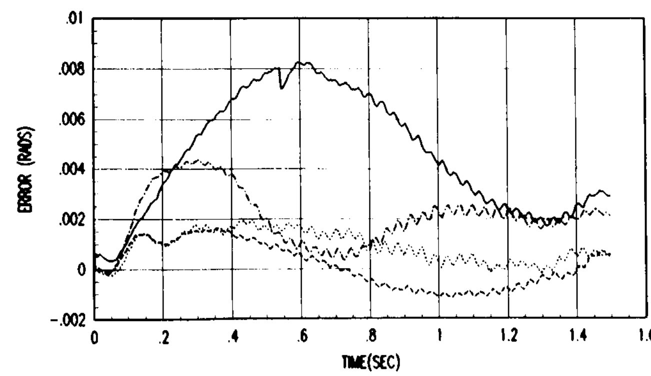

Figure 2: Joint 2 Tracking Evaluation w/o Payload

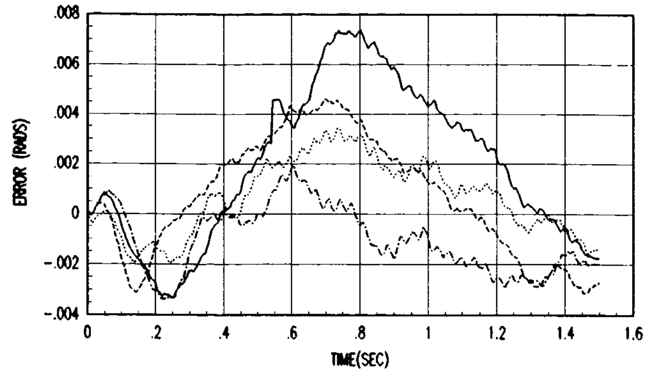

Figure 3: Joint 3 Tracking Evaluation w/o Payload

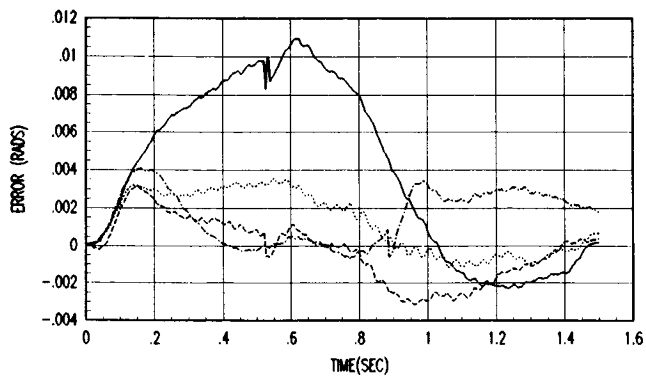

Figure 4: Joint 1 Tracking Evaluation with Payload

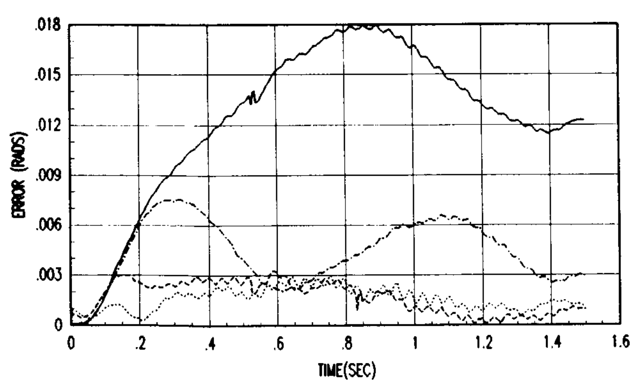

Figure 5: Joint 2 Tracking Evaluation with Payload

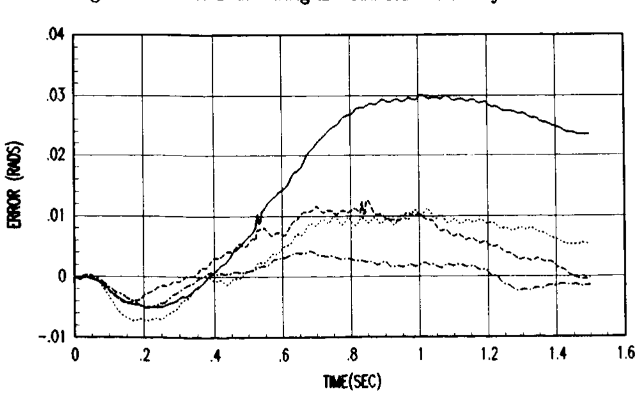

Figure 6: Joint 3 Tracking Evaluation with Payload

DATA KEY FOR FIGURES 1-6	
—	SMBC
···	MBQFT
- - -	MBAIC
-·-	AMBC

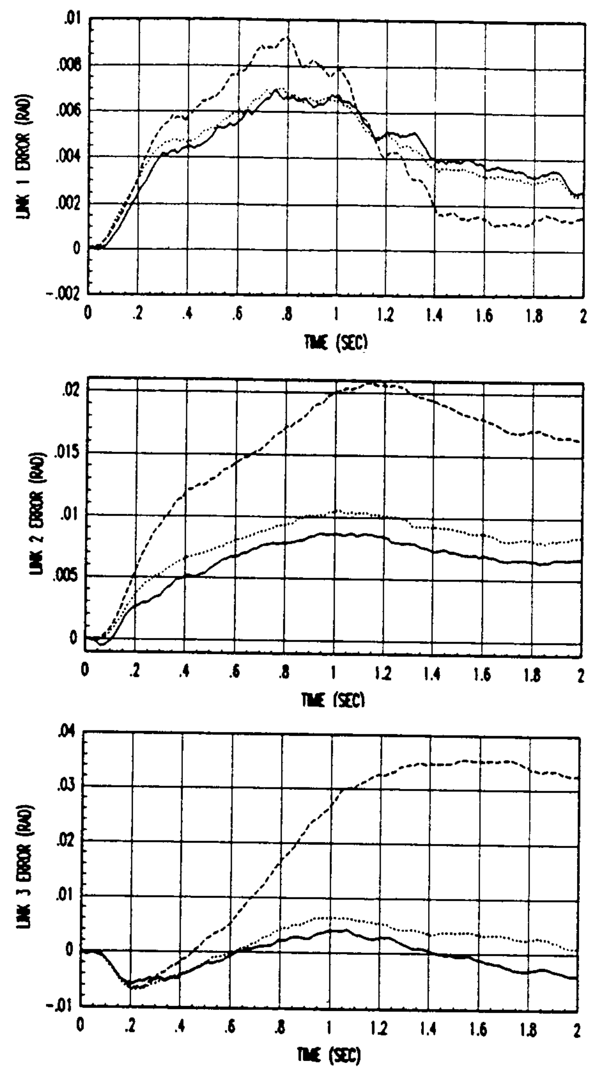

Figure 7: Tracking Evaluation with 3 Kg Payload

DATA KEY FOR FIGURE 7	
—	SMBC with Payload Info
···	MMBC
- - -	SMBC w/o Payload Info